

Whale optimisation algorithm for photovoltaic model identification

Omnia S. Elazab¹, Hany M. Hasanien¹, Mohamed A. Elgendy², Amr M. Abdeen¹

¹Electrical Power and Machines Department, Faculty of Engineering, Ain Shams University, Cairo 11517, Egypt

²School of Electrical and Electronic Engineering, Newcastle University, NE1 7RU, UK

E-mail: hanyhasanien@ieee.org

Published in *The Journal of Engineering*; Received on 11th October 2017; Accepted on 8th November 2017

Abstract: Parameter extraction of a solar cell is essential in the simulation and design calculation of photovoltaic (PV) systems. The mathematical model of the PV module is a non-linear I - V characteristic including several unknown parameters as the PV manufacturers' data are not sufficient. This study presents a method for estimating the parameters of the single- and double-diode PV models of a PV module based on a nature-inspired meta-heuristic optimisation algorithm known as the whale optimisation algorithm (WOA). The validity of the proposed WOA-based PV model is verified by comparing its simulation results with the experimental results for the PV modules under different environmental conditions.

1 Introduction

The solar energy is one of the most promising renewable sources. PV modules have short time of installation, long life of utilisation, simple circuitry and low maintenance requirements [1]. The costs of PV systems are continuously decreasing which allowed the global installed capacity to exceed 300 GW by the end of 2016 with a market growth of over 40% for the last 15 years [2].

To accurately simulate PV systems, it is essential to select a model that closely resembles the characteristics of PV cells [3]. The mathematical model of the PV module is non-linear and complex [4]. Despite the non-linearity, an accurate estimation of the cell parameters required for accurate performance evaluation. Several models have been introduced to describe the current voltage relationship [5]. In practice, there are two main equivalent circuit models used to describe the non-linear I - V relationship: single- and double-diode models.

The main parameters that describe the PV module behaviour are the generated photocurrent, saturation current, series resistance, shunt resistance, and the diode ideality factor [6]. Different methods are used to extract the parameters of PV modules, generally are assorted into (i) analytical and numerical approaches [7–11] or (ii) soft computing and evolutionary algorithms (EAs) [12–15]. Analytical and numerical approaches cannot provide precise values as PV models are highly non-linear, multi-variable, and multi-modal problems with many local optima. On the other hand, EA is a very effective choice for extracting the module parameters. Different EA techniques such as genetic algorithm [12] simulated annealing [13] and particle swarm optimisation [14, 15] have been applied for parameter extraction of solar module parameters.

More recently, the whale optimisation algorithm (WOA) has been presented by Seyedali and Andrew [16]. It is a meta-heuristic optimisation technique, which is based on observing, imitating, and modelling the special hunting method of a group of the humpback whales. This foraging behaviour is called the bubble-net feeding method [17]. Several engineering optimisation problems have been solved by the WOA [16]. The WOA can be considered as a global optimiser because it includes exploration/exploitation ability.

In this paper, a novel approach based on the WOA technology is presented with the purpose of determining the unknown parameters of the single- and double-diode PV models. The parameter

estimation method minimises the differences between calculated current and measured data by adjusting parameters of the PV models. The fitness value is evaluated by the root mean square (RMS) error [18]. The validity of the proposed PV model is verified by the simulation results, which are performed under different temperature and irradiation conditions.

The paper is organised as follows: Section 2 describes the mathematical model of the PV module. In Section 3, the problem formulation is introduced. Section 4 presents the WOA. In Section 5, the simulation results and discussion are presented. Finally, Section 6 draws the conclusion.

2 Model of PV module

Many equivalent circuit models have been proposed to describe the I - V characteristics of the solar cell. In practice, two main circuit models: single-diode model and double-diode model are commonly used.

2.1 Single-diode model

The single-diode model is considered due to its simplicity and accuracy [19]. It includes a current source, one diode and two resistors as shown in Fig. 1.

The output current of the module is calculated as

$$I = I_{PV} - I_0 \left\{ \exp \left[\frac{(V + IR_s)}{\alpha V_{th}} \right] - 1 \right\} - \frac{V + IR_s}{R_p} \quad (1)$$

where I_{PV} is the photovoltaic (PV) current, I_0 is the reverse saturation current of the diode, α is the ideality factor of the diode, and $V_{th} = N_s k T / q$ is the thermal voltage of the module. N_s is the number of series connected PV cells in the module, k is the Boltzmann constant, q is the electron charge, and T is the temperature of the p - n junction in Kelvin. R_s and R_p are the series and shunt resistance, respectively, and V is output voltage of the module. For the single-diode model, five parameters are extracted, which are I_{PV} , I_0 , R_s , R_p , and α .

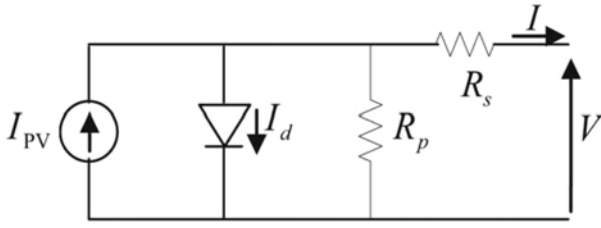


Fig. 1 Single-diode model of the PV module

2.2 Double-diode model

The two-diode model is a more accurate model that takes the effect of recombination losses in the space-charge into account by adding an additional diode. Fig. 2 shows the two-diode model.

In this case, the output current of the module is calculated as

$$I = I_{PV} - I_{O1} \left\{ \exp \left[\frac{(V + IR_S)}{\alpha_1 V_{th}} \right] - 1 \right\} - I_{O2} \left\{ \exp \left[\frac{(V + IR_S)}{\alpha_2 V_{th}} \right] - 1 \right\} - \frac{V + IR_S}{R_p} \quad (2)$$

I_{O1} and I_{O2} are the reverse saturation currents of diode 1 and diode 2, respectively. The I_{O2} term is introduced to compensate the recombination loss in the depletion region. Variables α_1 and α_2 are the diode ideality constants; α_1 and α_2 represent the diffusion and recombination current component, respectively. Although higher accuracy can be achieved using double-diode compared to the single-diode model, it requires the computation of seven parameters; I_{PV} , I_{O1} , I_{O2} , R_p , R_s , α_1 , and α_2 .

The dependence of all of the parameters on temperature and irradiance levels is considered [20, 21]

$$I_{PV} = (I_{pvn} + k_i T) \frac{G}{G_n} \quad (3)$$

$$I_o = I_{on} \left(\frac{T}{T_n} \right)^3 \exp \left[\frac{qE_g}{\alpha k} \left(\frac{1}{T_n} - \frac{1}{T} \right) \right] \quad (4)$$

$$E_g = E_{gn} (1 - 0.0002677 \Delta T) \quad (5)$$

$$R_p = R_{pn} \frac{G}{G_n} \quad (6)$$

where I_{pvn} , I_{on} , E_{gn} , G_n , R_p and T_n denote the photocurrent, diode saturation current, material band gap, solar irradiance, shunt resistance, and cell temperature measured at standard test conditions (STCs), respectively. E_{gn} is set to 1.121 eV for silicon cells [20], ΔT presents the difference between T and T_n . K_i represents the short-circuit current coefficient. By using these relations, the I - V characteristics of a PV module for different temperature and solar irradiance are described.

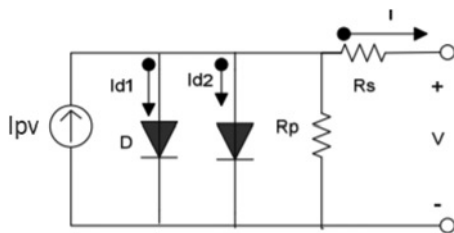


Fig. 2 Double-diode model of the PV module

3 Problem formulation

To extract the parameters of different PV models from the I - V data using the optimisation techniques, the objective function should be defined and optimised. In this work, the RMS error, which minimises the difference between real and estimated values, is used as the objective function and is described as

$$\varepsilon = \sqrt{\frac{1}{N} \sum_{k=1}^N f_k(V, I, \emptyset)} \quad (7)$$

where N is the number of experimental data samples, \emptyset is decision vector which consists of the parameters to be extracted. In case of single-diode model, the (V, I, \emptyset) is given by

$$f_k(V, I, \emptyset) = I_{PV} - I_O \left\{ \exp \left[\frac{(V + IR_S)}{\alpha V_{th}} \right] - 1 \right\} - \frac{V + IR_S}{R_p} - I \quad (8)$$

where $\emptyset = \{I_{PV}, I_O, R_S, R_p, \alpha\}$.

For the double-diode model, the function (V, I, \emptyset) is given as

$$f_k(V, I, \emptyset) = I_{PV} - I_{O1} \left\{ \exp \left[\frac{(V + IR_S)}{\alpha_1 V_{th}} \right] - 1 \right\} - I_{O2} \left\{ \exp \left[\frac{(V + IR_S)}{\alpha_2 V_{th}} \right] - 1 \right\} - \frac{V + IR_S}{R_p} - I \quad (9)$$

where $\emptyset = \{I_{PV}, I_{O1}, I_{O2}, R_S, R_p, \alpha_1, \alpha_2\}$

The aim of the study is to minimise (8) and (9) with respect to \emptyset . The WOA is applied to the objective function to obtain the unknown parameters of the single- and double-diode models.

4 Whale optimisation algorithm (WOA)

The WOA is a new meta-heuristic optimisation algorithm mimicking the hunting behaviour of humpback whales. An adult humpback whale is as big as a school bus. Fig. 3 shows this mammal. The special thing about the humpback whales is their way of hunting known as the bubble-net feeding method [17]. Humpback whales prefer to hunt school of krill or small fishes near the surface.

Humpback whales go down around 12 m down in water then start to produce bubbles in a spiral shape or '9'-shaped path encircles prey then follows the bubbles and moves upward the surface to catch the prey [22]. Fig. 3 represents this bubble net behaviour. The humpback whales work in teams of at least two individuals and are not beyond stealing prey from the bubble nets set up by others [23]. Bubble-net feeding is a unique behaviour noticed in humpback whales.

The mathematical model of encircling prey, bubble net hunting method, search for the prey is described in the following 3 subsections:



Fig. 3 Bubble-net feeding behaviour in humpback whales [16]

4.1 Encircling prey equation

Humpback whales can notice the prey location and en-circle them, the WOA supposes that target prey is the current best solution. Then the best search agent is defined, accordingly other search agents will update their positions towards the best search agent over the course of increasing number of iteration from start to a maximum number of iteration through the following equations:

$$D = |C \cdot X^*(t) - X(t)| \quad (10)$$

$$X(t+1) = X^*(t) - A \cdot D \quad (11)$$

where t indicates the current iteration, A and C are coefficient vectors, X^* is the position vector of the best solution obtained so far, X is the position vector. X^* should be updated in each iteration, if there is a better solution. The coefficient vectors A and C are calculated as follows:

$$A = 2 \cdot a \cdot r - a \quad (12)$$

$$C = 2 \cdot r \quad (13)$$

where a is a variable linearly decrease from 2 to 0 over the iterations in both exploration and exploitation phases. Exploration is related to global search exploring the search space looking for good solutions while exploitation is related to local search to refine the solution avoiding big jumps on the search space. r is a random number $[0, 1]$.

4.2 Bubble-net attacking method

To develop the mathematical equations for bubble-net behaviour of humpback whales, two methods are modelled as follows:

- Shrinking encircling mechanism:** This technique is employed by decreasing linearly the value of a from 2 to 0 over the course of iterations in (12), causing fluctuation in A in the interval $[-1, 1]$. The new position of a search agent is anywhere between the original position of the agent and the position of the current best agent. Fig. 4 shows the possible positions from (X, Y) towards (X^*, Y^*) that can be achieved by $0 \leq A \leq 1$ in a 2D space.
- Spiral updating position:** To update the position of whale located at (X, Y) and prey located at (X^*, Y^*) , a spiral equation is introduced to mimic the helix-shaped movement of humpback whales as shown in Fig. 4b, which is described as

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) \quad (14)$$

where $D' = |X^*(t) - X(t)|$ and indicates the distance of the i th whale to the prey (best solution obtained so far), b is a constant

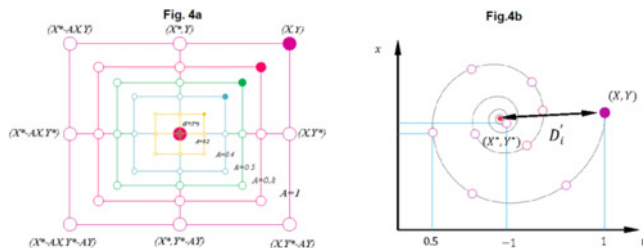


Fig. 4 Bubble-net search mechanism implemented in WOA (X^* is the best solution obtained so far)
a Shrinking encircling mechanism
b Spiral updating position [16]

Table 1 Typical electrical characteristics of PV module under STC

I_{sc}	8.21 A
V_{oc}	32.9 V
I_{mp}	7.61 A
V_{mp}	7.61 A
P_{max}	200 W
K_v	-0.123 V/°C
K_i	0.00318 A/°C
N_s	54

for defining the shape of the logarithmic spiral, l is a random number in $[-1, 1]$.

There is a probability of 50% to choose either the shrinking encircling mechanism or the spiral model to update the position of whales

$$X(t+1) = \begin{cases} X^*(t) - A \cdot D & \text{if } p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) & \text{if } p > 0.5 \end{cases} \quad (15)$$

where p expresses random number between $[0, 1]$.

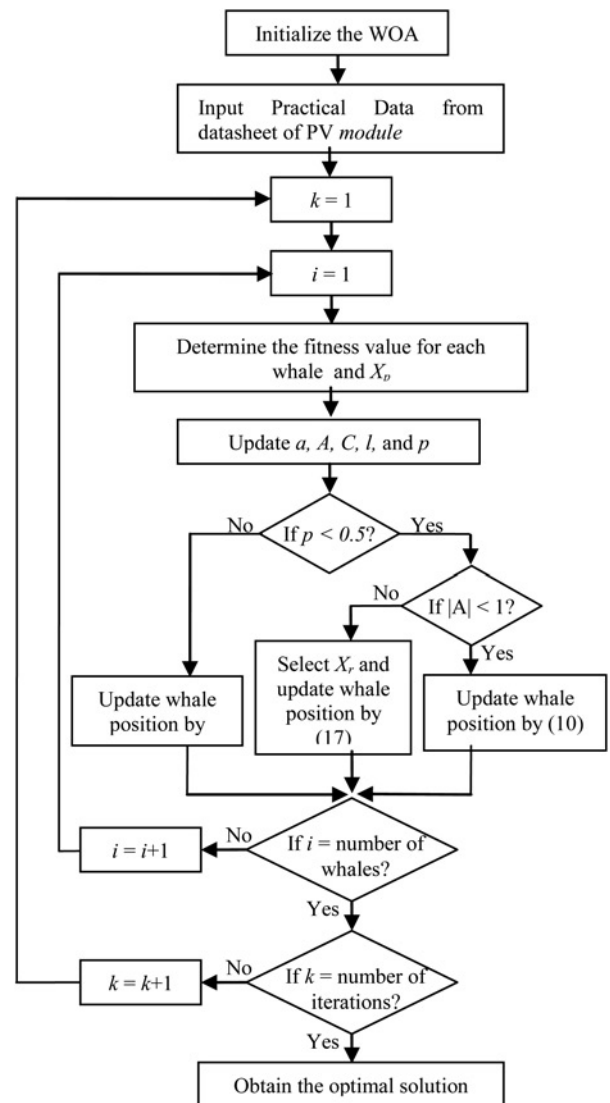


Fig. 5 Flow chart of the WOA algorithm

4.3 Search for prey

Exploration is expressed as follows :

$$D = |C \cdot X_{\text{rand}} - X| \quad (16)$$

$$X(t+1) = X_{\text{rand}} - A \cdot D \quad (17)$$

Vector A takes the values >1 to enforce exploration.

5 Simulation results

In this study, Kyocera polycrystalline KC200GT is used to test the WOA-based PV model. The typical electrical characteristics of these PV modules under the STC (module temperature, 25°C, AM 1.5 spectrum, irradiance 1000 W/m²) are listed in Table 1. According to the WOA presented in Section 4, the WOA starts with a set of random solutions. At each iteration, search agents update their positions with respect to either a randomly chosen search agent or the best solution obtained so far. Then a parameter is decreased from 2 to 0 to provide exploration and exploitation. A random search agent is chosen when $|A| > 1$, while the best solution is selected when $|A| < 1$ for updating the position of the search agents. Depending on the value of p , WOA switches between either spiral or circular movement. Finally, the WOA is terminated by the satisfaction of a termination criterion. The flowchart of the WOA approach is shown in Fig. 5.

In this study, The WOA was terminated after pre-specified number of iterations. Number of iterations was set to 500 and number of search agents was set 30. It can be noted that the WOA has the merit of high speed convergence, which is clearly shown in Fig. 6 taking about 2.8 s. The simulation results are performed using an Intel(R) Core(TM) i3 CPU M380@ 2.53 GHz Processor, 2 GB RAM, 64-bit operating system, PC. The WOA code is built using MATLAB environment.

The proposed PV model for single-diode model using the WOA is tested by making a comparison with the model using the

iterations method [24] and the GA method presented in [25]. The results are shown in Table 2.

Similarly, the proposed optimal PV model for double-diode PV model using the WOA is tested by making a comparison among the model using particle swarm optimisation (PSO), genetic algorithm (GA) and the WOA-based PV model for KC200GT PV module. The results are shown in Table 3 [26].

Table 2 Comparison of optimum single-diode for KC200GT PV module

Method	Iteration	GA	WOA
I_{pv} , A	8.214	8.213	8.029
I_{o1} , A	9.825×10^{-8}	8.789×10^{-8}	8.558×10^{-8}
R_s , Ω	0.221	0.232	0.2815
R_{p1} , Ω	0.2485	547.91	424.22
α	1.3	1.29	1.216

Table 3 Comparison of optimum double-diode for KC200GT PV module

Method	GA	PSO	WOA
I_{o1} , A	2.15×10^{-8}	2.71×10^{-8}	1.915×10^{-8}
I_{o2} , A	4.13×10^{-10}	4.13×10^{-10}	3.729×10^{-10}
R_s , Ω	0.303	0.2235	0.2745
R_{p1} , Ω	343.10	298.77	291.4
α_1	1.2	1.21	1.201
α_2	1	1	1.107
I_{pv} , A	8.21	8.21	8.146

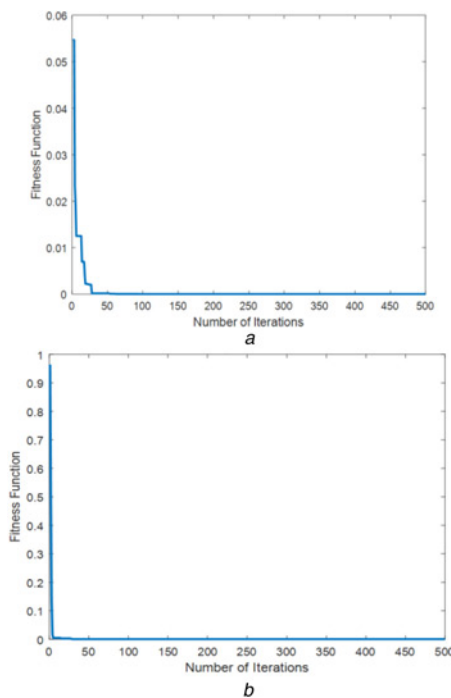


Fig. 6 Fitness function convergence
a Single diode
b Double diode

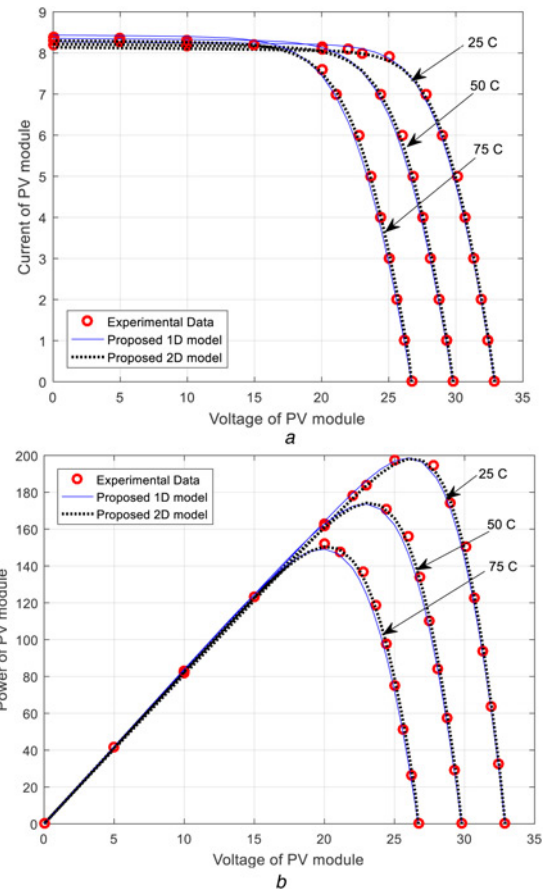


Fig. 7 Simulation results and experimental data of the KC200GT PV module under different temperature conditions, $G = 1000 \text{ W/m}^2$
a I - V curves
b P - V curves

It can be realised that the values of the unknown parameters of the PV models using the WOA are close to that of other different methods and they are also in an acceptable range.

To show the superiority of the proposed method, the validity of the proposed WOA-based PV model is verified by comparing the simulation results with the experimental results for the PV modules under different environmental conditions. Fig. 7 and Fig. 8 show the $I-V$ curves, power versus voltage ($P-V$) curves, and the experimental data of the KC200GT PV module under

different temperature conditions for single-diode model and double-diode model, respectively. It can be demonstrated that the $I-V$ and $P-V$ curves of the proposed WOA-based PV model coincide with the experimental data. This distinguishes the high accuracy of the proposed PV model. Double-diode model proved to be more accurate than single-diode except at low irradiance level.

For more verification of the proposed WOA-based PV model, the absolute current error of the proposed PV model with respect to the experimental data is compared with the absolute current error of the iterations-based PV model [8] and a MATLAB PV model [27] as shown in Fig. 9. It can be noted that the absolute current error of the WOA-based PV model is lower than that of other PV models.

6 Conclusion

This paper proposed a method for identifying the parameters of the electrical equivalent circuits of the PV modules. The identified model is essential to simulate the behaviour of the PV modules at any operating condition. The mathematical model of the PV module is a non-linear $I-V$ characteristic that includes several unknown parameters because of the limited information provided by the PV manufacturers. The optimised problem under study was formulated using root mean square error between the module current and the computed current. The objective of the optimised problem was to minimise the RMS error function. The WOA was successfully applied to solve the optimised problem producing the unknown parameters of the PV model for both single- and double-diode methods. The results were verified by comparing the experimental and numerical values of $I-V$ and $P-V$ characteristic curves under STC and under different temperatures and irradiances. The simulation results of the WOA-based PV model coincide with the experimental data. The results obtained demonstrate that the proposed models are close to that of other different methods and they are also in an acceptable range. Double-diode model proved to be more accurate than single-diode in particular at low irradiance level.

7 References

- [1] Meekki H., Mellit A., Sall H.: 'Modeling and simulation of photovoltaic panel based on artificial neural networks and VHDL-language'. 4th Int. Conf. on Computer Integrated Manufacturing CIP, Sétif, Algeria, 2007
- [2] Jäger-Waldau A.: 'PV status report 2016', Publications Office of the European Union, October 2016, ISBN 978-92-79-63055-2
- [3] Hasanien H.M., Mueen S.M., Al-Durra A.: 'Gravitational search algorithm-based photovoltaic array reconfiguration for partial shading losses reduction', Proc. IET Renewable Power Generation Conf., RPG2016, London, U.K., 21–23 September 2016, pp. 1–6
- [4] Hasanien H.M.: 'Shuffled frog leaping algorithm for photovoltaic model identification', *IEEE Trans. Sustain. Energy*, 2015, **6**, (2), pp. 509–515
- [5] Wolf M., Noel G., Stirn R.: 'Investigation of the double exponential in the current-voltage characteristics of silicon solar cells', *IEEE Trans. Electron. Devices*, 1977, **24**, (4), pp. 419–428
- [6] AlHajri M.F., El-Naggar K.M., AlRashidi M.R., ET AL.: 'Optimal extraction of solar cell parameters using pattern search', *Renew. Energy*, 2012, **44**, pp. 238–245
- [7] Ortiz-Conde A., García Sánchez F.J., Muci J.: 'New method to extract the model parameters of solar cells from the explicit analytic solutions of their illuminated $I-V$ characteristics', *Sol. Energy Mater. Sol. Cells*, 2006, **90**, pp. 352–361
- [8] Villalva M.G., Gazoli J.R., Filho E.R.: 'Comprehensive approach to modeling and simulation of photovoltaic arrays', *IEEE Trans. Power Electron.*, 2009, **24**, (5), pp. 1198–1208
- [9] Chegaar M., Ouennoughi Z., Guechi F.: 'Extracting dc parameters of solar cells under illumination', *Vacuum*, 2004, **75**, pp. 367–372
- [10] Chegaar M., Azzouzi G., Mialhe P.: 'Simple parameter extraction method for illuminated solar cells', *Solid-State Electron.*, 2006, **50**, pp. 1234–1237
- [11] Haouari-Merbah M., Belhamel M., Tobias I., ET AL.: 'Extraction and analysis of solar cell parameters from the illuminated current-voltage curve', *Sol. Energy Mater. Sol. Cells*, 2005, **87**, pp. 225–233

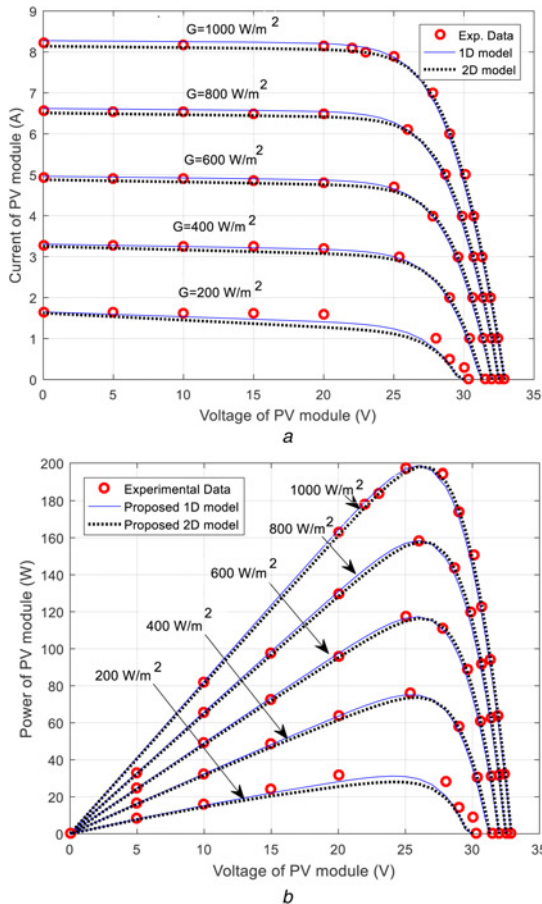


Fig. 8 Simulation results and experimental data of the KC200GT PV module under different irradiation conditions, actual temperature = 25°C
a $I-V$ curves
b $P-V$ curves

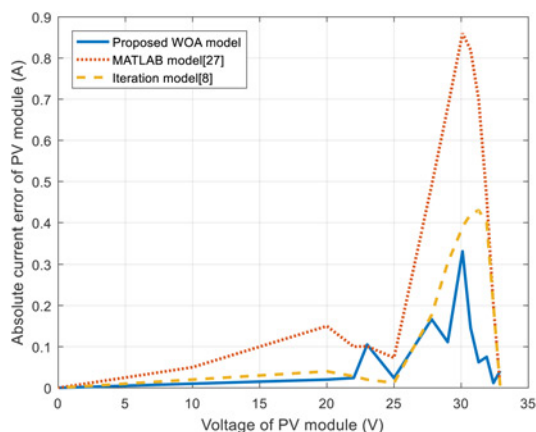


Fig. 9 Absolute current error of PV module

- [12] Zagrouba M., Sellami A., Bouaïcha M., *ET AL.*: 'Identification of PV solar cells and modules parameters using the genetic algorithms: application to maximum power extraction', *Sol. Energy*, 2010, **84**, pp. 860–866
- [13] Asif S.: 'Solar cell modeling and parameter optimization using simulated annealing', *J. Propuls. Power*, 2008, **24**, pp. 1018–1022
- [14] Wei H., Cong J., Lingyun X., *ET AL.*: 'Extracting solar cell model parameters based on chaos particle swarm algorithm'. *Electric Information and Control Engineering (ICEICE)*, Wuhan, China, 2011, pp. 398–402
- [15] Sandrolini L., Artioli M., Reggiani U.: 'Numerical method for the extraction of photovoltaic module double-diode model parameters through cluster analysis', *Appl. Energy*, 2010, **87**, pp. 442–451
- [16] Seyedali M., Andrew L.: 'The whale optimization algorithm', *Adv. Eng. Softw.*, 2016, **95**, pp. 51–67
- [17] Watkins WA., Schevill WE.: 'Aerial observation of feeding behavior in four baleen whales: *Eubalaena glacialis*, *Balaenoptera borealis*, *Megaptera novaeangliae*, and *Balaenoptera physalus*', *J. Mammal*, 1979, **60**, pp. 155–163
- [18] Ishaque K., Salam Z., Mekhilef S., *ET AL.*: 'Parameter extraction of solar photovoltaic modules using penalty-based differential evolution', *Appl. Energy*, 2012, **99**, pp. 297–308
- [19] Hasanien H.M.: 'An adaptive control strategy for low voltage ride through capability enhancement of grid-connected photovoltaic power plants', *IEEE Trans. Power Syst.*, 2016, **31**, (4), pp. 3230–3237
- [20] Soto W. De, Klein S., Beckman W.: 'Improvement and validation of a model for photovoltaic array performance', *Sol. Energy*, 2006, **80**, (1), pp. 78–88
- [21] Sera D., Teodorescu R., Rodriguez P.: 'PV panel model based on datasheet values'. *Proc. IEEE Int. Symp. on Industrial Electronics*, Vigo, Spain, 2007, pp. 2392–2396
- [22] Goldbogen JA., Friedlaender AS., Calambokidis J., *ET AL.*: 'Integrative approaches to the study of baleen whale diving behavior, feeding performance, and foraging ecology', *Bioscience*, 2013, **63**, pp. 90–100
- [23] Humpback whales make bubble nets with beauty and precision by EarthSky in EARTH | June 27, 2011, available at <http://earthsky.org/earth/humpback-whales-make-bubble-nets-with-beauty-and-precision>
- [24] Villalva M.G., Gazoli J.R., Filho E.R.: 'Comprehensive approach to modeling and simulation of photovoltaic arrays', *IEEE Trans. Power Electron.*, 2009, **24**, (5), pp. 1198–1208
- [25] Dizqah A.M., Krishna A.M., Busawon K.: 'An accurate method for the PV model identification based on a genetic algorithm and the interior point method', *Renew. Energy*, 2014, **72**, pp. 212–222
- [26] Jacoba B., Balasubramanian K., Sudhakar Babu T.S., *ET AL.*: 'Solar PV modelling and parameter extraction using artificial immune system a school of electrical engineering'. 7th Int. Conf. on Applied Energy – ICAE2015, VIT University, Vellore, Tamil Nadu, 632014, India, 2015
- [27] Walker G.: 'Evaluating MPPT converter topologies using a MATLAB PV model', *J. Electr. Electron. Eng.*, 2001, **21**, (1), pp. 45–55